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PADDY FIELDS DETECTION ON Sentinel-2 SATELLITE IMAGES USING EfficientDet MODEL

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Abstract. *Agricultural monitoring plays an important role in ensuring food security and sustainable farming practices. This project focuses on the task of paddy field detection on the satellite images collected from the agricultural lands of Andhra Pradesh. Using satellite images of Sentinel-2 and deep learning techniques, our approach aims to improve the accuracy and efficiency of paddy land identification. The project employs a deep learning model, which is the EfficientDet trained on a carefully annotated dataset, to detect the paddy fields in the region. The utilization of remote sensing technology allows for scalable and timely monitoring across vast agricultural lands. The selected model architecture, combined with fine-tuning strategies, ensures adaptability to the unique spatial and seasonal characteristics of South Indian agriculture. Results from the project showcase the capability of the proposed approach in accurately identifying and detecting paddy crops. The integration of advanced technologies for precision agriculture contributes to informed decision-making, resource optimization, and overall sustainability in the farming sector. To collect the ground truth data, we used the AP GIS portal, which is supervised by the Andhra Pradesh agriculture department, which has the data of the percentage of paddy lands in small villages. The places with more than 95 percent of paddy lands are selected for better data samples. The collected samples are cropped and labelled, and trained on the model architecture and verified for accuracy. This project not only advances the field of agricultural monitoring but also holds significant importance for crop management and supporting the livelihoods of farmers of our state. The proposed model achieved an accuracy of 86%, demonstrating its reliability in detecting paddy fields from Sentinel-2 satellite imagery.*

Keywords: agricultural monitoring, deep learning, crop detection, paddy, Andhra Pradesh region, Sentinel-2

WYKRYWANIE PÓL RYŻOWYCH NA OBRAZACH SATELITARNYCH Sentinel-2 ZA POMOCĄ MODELU EfficientDet

Streszczenie. *Monitorowanie rolnictwa odgrywa kluczową rolę w zapewnieniu bezpieczeństwa żywnościowego i zrównoważonych praktyk rolniczych. Niniejszy projekt koncentruje się na wykrywaniu pól ryżowych na obrazach satelitarnych zebranych z terenów rolniczych stanu Andhra Pradesh. Wykorzystując obrazy Sentinel-2 oraz techniki głębokiego uczenia, nasze podejście poprawia dokładność i efektywność identyfikacji terenów uprawnych ryżu. Model EfficientDet, przeszkolony na starannie oznakowanym zbiorze danych, umożliwia skuteczne wykrywanie pól ryżowych, a zastosowanie technologii teledetekcji pozwala na skalowalne i terminowe monitorowanie rolnictwa. Wybrana architektura modelu, w połączeniu ze strategiami dostrajania, zapewnia dostosowanie do unikalnych cech przestrzennych i sezonowych rolnictwa południowych Indii. Wyniki projektu potwierdzają skuteczność proponowanego podejścia w precyzyjnym wykrywaniu upraw ryżu. W celu zebrania danych referencyjnych wykorzystano portal AP GIS nadzorowany przez Departament Rolnictwa Andhra Pradesh, który zawiera informacje o procentowym udziale pól ryżowych w małych wsiach. Do analizy wybrano miejsca, gdzie pola ryżowe stanowią ponad 95% powierzchni, co pozwoliło uzyskać wysokiej jakości próbki danych. Zebrane próbki zostały przycięte, oznaczone, przeszkolone na architekturze modelu i zweryfikowane pod kątem dokładności. Projekt ten nie tylko przyczynia się do rozwoju monitorowania rolnictwa, ale także ma istotne znaczenie dla zarządzania uprawami oraz wspierania środków utrzymania rolników w naszym stanie. Proponowany model osiągnął dokładność na poziomie 86%, co potwierdza jego niezawodność w wykrywaniu pól ryżowych na obrazach satelitarnych Sentinel-2.*

Słowa kluczowe: monitorowanie rolnictwa, głębokie uczenie, wykrywanie upraw, ryż, region Andhra Pradesh, Sentinel-2

Introduction

Crop Land detection relies on the power of satellite imagery and machine learning. Satellites capture high-resolution images of the Earth's surface, revealing subtle variations in colour and texture that differentiate different crop types. Machine learning algorithms, particularly neural networks, are then trained to analyse these vast datasets and identify patterns that distinguish paddy fields and other crops from surrounding vegetation. The future of crop type mapping holds immense potential for a more sustainable and productive agricultural sector. Sentinel-2 Satellite data Sentinel-2 satellites capture images with a resolution of 10 meters for most bands, providing detailed information about the land surface. This allows the machine learning model to distinguish between paddy and cotton fields, which might have subtle visual differences. Cost-Effectiveness: Sentinel-2 data is freely available from the European Space Agency (ESA), making it a cost-effective choice for your project compared to purchasing commercial satellite imagery. Temporal Coverage: Sentinel-2 satellites revisit the same area every 5 days, providing frequent updates on the state of crops. This allows you to monitor changes in crop growth and health throughout the season. GEE Integration: Sentinel-2 data is readily accessible and processable within Google Earth Engine, a cloud-based platform specifically designed for geospatial analysis. This simplifies data access, pre-processing, and integration with machine learning models for crop type mapping. AP GIS-PORTAL The Andhra Pradesh GIS Portal is a comprehensive platform developed by the Government of Andhra Pradesh to integrate, manage, and utilize geospatial data for planning, governance, and development purposes. The portal serves as a crucial tool for various government departments, organizations, and public users to access and use geospatial information for informed decision-making. The aim of the project titled "Paddy Cropland Detection Using Sentinel-2 Satellite images for Andhra Pradesh region" is to develop a precise and efficient model for identifying and detecting paddy crops in the agricultural regions of Andhra Pradesh using advanced machine learning techniques. The motivation for this project is that our country has 394.6 million acres of agricultural land (the second biggest) in the world, with a predominant focus on the cultivation of paddy. The project seeks to address the challenges in traditional monitoring methods that lack precision and scalability. By using the capabilities of deep learning and remote sensing technologies, the project aims to develop a tool for accurately identifying and monitoring crop patterns. The ultimate objective is to enhance agricultural productivity, reduce resource wastage, and contribute to the overall sustainability of agriculture in the specified geographic context of South India (AP). The Objectives of our project are:

1. Collect the Sentinel-2 data for the crop seasons in AP using the information from the AP GIS portal and Google Earth Engine, and Google Earth Pro, ESA, for different stages of paddy growth.
2. Apply the pre-processing techniques, like reducing the size of the dataset and converting the images to a suitable form.
3. Apply the deep learning techniques, like a model architecture, to train the model for feature extraction.
4. Testing the model performance on various samples of images and ensuring of having a high accuracy.

1. Literature review

This chapter contains the list of research papers that we have studied under the literature survey. We focused on the approaches for maintaining accuracy in these papers. Our study included the techniques used for developing and training the model. In [1], Ajadi et al. conducted a large-scale crop type and crop area mapping study across Brazil using synthetic aperture radar (SAR) and optical imagery. Their research highlights the importance of integrating multi-sensor remote sensing data to enhance agricultural monitoring and classification accuracy. By leveraging SAR data, which is resilient to cloud cover and weather conditions, alongside optical imagery, the study effectively mapped various crop types across extensive agricultural regions. The proposed approach employed machine learning algorithms to classify crops with high precision, ensuring reliable and scalable agricultural mapping. The results demonstrated that combining SAR and optical data significantly improved classification accuracy, particularly in regions where cloud contamination limits optical sensor effectiveness. This research underscores the potential of multi-source satellite data in advancing precision agriculture, supporting better decision-making for sustainable farming practices, and enhancing large-scale crop monitoring efforts.

Ding et al. [2] proposed a phenology-based rice paddy mapping method that integrates multi-source satellite imagery with a fusion algorithm, applied to the Poyang Lake Plain in Southern China. The study leverages temporal variations in vegetation indices to detect rice paddies based on their distinct growth cycles. By utilizing multi-source satellite data, the approach mitigates challenges associated with cloud contamination and ensures more reliable mapping of rice fields. The fusion algorithm combines optical and synthetic aperture radar (SAR) data, enhancing the ability to distinguish rice paddies from other land cover types. The study demonstrates that by analysing phenological changes, such as the transplanting and harvesting phases, the mapping accuracy is significantly improved. The results show high classification accuracy, proving the effectiveness of using phenological characteristics for precision agriculture. This research provides valuable insights into temporal-based crop monitoring and serves as a relevant reference for paddy field detection using multi-source remote sensing data. The methodology presented by Ding et al. aligns well with modern deep learning approaches, where time-series satellite data and fusion techniques can enhance classification accuracy for large-scale agricultural mapping.

Gumma et al. [3] conducted a remote sensing-based change analysis of rice environments in Odisha, India, to assess the spatial and temporal variations in paddy cultivation. The study utilized multi-temporal satellite imagery to monitor changes in rice-growing areas, enabling a better understanding of cropping patterns and environmental impacts. By integrating remote sensing data with geographic information systems (GIS), the research identified significant shifts in rice cultivation, influenced by factors such as climate variability, water availability, and land-use changes. The analysis demonstrated how satellite-based monitoring can provide critical insights into the sustainability of rice farming and support informed decision-making for agricultural planning. The findings emphasized the importance of remote sensing in tracking long-term trends in paddy cultivation, ensuring food security, and optimizing resource management in rice-growing regions.

Hedayati et al. [4] investigated the effectiveness of Landsat-8 satellite imagery combined with an object-based classification approach for detecting paddy lands in Rasht City, Iran. The study focused on enhancing classification accuracy by utilizing spectral, textural, and spatial attributes to distinguish paddy fields from other land cover types. Unlike traditional pixel-based classification, the object-based method segmented images into meaningful regions, improving the identification of agricultural areas with complex structures. The study demonstrated that object-based classification significantly improved the detection precision of paddy fields by reducing misclassification caused by spectral similarities with non-agricultural land. Additionally, the integration of multi-temporal Landsat-8 images allowed for the monitoring of seasonal variations in rice cultivation, making the approach highly relevant for large-scale agricultural mapping. The results highlighted the potential of remote sensing and object-based image analysis in supporting sustainable agricultural management, particularly for rice-growing regions that require continuous monitoring and efficient land-use planning.

Mahabbah [5] explored rice field detection and mapping using multitemporal Sentinel-1 synthetic aperture radar (SAR) data in three districts of Cianjur, Indonesia. The study employed an RGB composite and thresholding approach to enhance the identification of rice fields in varying environmental conditions. Unlike optical satellite imagery, which is often hindered by cloud cover, Sentinel-1 SAR data provided reliable observations regardless of weather conditions, making it highly suitable for continuous agricultural monitoring. The RGB composite technique utilized different polarization bands to highlight rice paddies, while the thresholding method effectively distinguished cultivated areas based on backscatter intensity variations corresponding to different rice growth stages. The study demonstrated that the integration of SAR data with these analytical techniques significantly improved classification accuracy, ensuring precise detection of rice fields in diverse landscapes. The findings underscore the potential of SAR-based methodologies for large-scale rice mapping, supporting agricultural planning and food security initiatives in regions where cloud-free optical imagery is often unavailable.

Neforawati et al. [6] present an innovative approach to precision agriculture by employing Convolutional Neural Networks (CNNs) for classifying paddy crop growth stages. The study emphasizes the importance of automated and data-driven solutions in modern farming to enhance crop monitoring efficiency. Traditional techniques for assessing paddy growth often rely on spectral indices and manual observations, which are not only intensive but also subject to human errors and environmental variations. By leveraging deep learning techniques, particularly CNNs, the researchers developed a model capable of analysing high-resolution images from satellite and UAV sources to classify different paddy growth levels accurately. Their findings suggest that CNNs can effectively extract relevant features from multispectral and RGB images, significantly improving classification accuracy compared to conventional machine learning methods. The study also explores various CNN architectures, optimizing hyperparameters to maximize detection performance. The proposed model demonstrates robust scalability, allowing for large-scale monitoring of paddy fields with minimal human intervention. Moreover, the integration of deep learning models into precision agriculture systems could revolutionize farm management by providing real-time insights, enabling farmers to optimize irrigation, fertilization, and harvesting schedules. The research highlights how CNN-based classification can contribute to sustainable farming practices by reducing resource wastage and enhancing yield prediction. Ultimately, this study reinforces the growing potential of deep learning in agricultural applications, offering an efficient and scalable solution for monitoring paddy crops throughout their growth cycle.

Pott et al. [7] investigated satellite-based data fusion techniques for crop type classification and mapping in Rio Grande do Sul, Brazil. The study leveraged multi-source remote sensing data, integrating optical imagery and synthetic aperture radar (SAR) data to enhance classification accuracy across diverse agricultural landscapes. By employing advanced machine learning algorithms, the research demonstrated that data fusion significantly improves the differentiation between crop types, particularly in regions with complex land cover and seasonal variations. The study highlighted the effectiveness of combining spectral, temporal, and radar backscatter features to mitigate challenges posed by cloud cover, ensuring consistent crop monitoring. The results showed a high overall classification accuracy, emphasizing the potential of satellite-based fusion approaches for large-scale agricultural mapping. This research contributes to precision agriculture by enabling more reliable assessments of crop distribution, ultimately supporting sustainable farming practices and agricultural resource management in Brazil.

Sass and Cicerone [8] explored the allocation of photosynthates in rice plants, analysing the balance between food production and methane emissions in paddy fields. Their study highlighted the dual role of rice cultivation, where carbon assimilation not only supports grain yield but also contributes to methane production due to anaerobic soil conditions. The research provided critical insights into how rice plants allocate energy resources, influencing both agricultural productivity and greenhouse gas emissions. By understanding the biochemical pathways involved, the study emphasized the need for sustainable rice farming practices that optimize yield while minimizing environmental impact. Their findings remain significant in discussions on climate change mitigation strategies within the agricultural sector.

Teixeira et al. [9] provided a comprehensive review of deep learning models for crop classification in aerial imagery, highlighting the advancements and challenges in the field. The study examined various neural network architectures, including convolutional neural networks (CNNs) and transformer-based models, emphasizing their effectiveness in processing high-resolution remote sensing data. The review discussed key factors influencing classification accuracy, such as spectral and spatial feature extraction, dataset availability, and the role of data augmentation techniques. Additionally, the study explored the integration of multi-temporal and multi-source imagery to enhance model robustness and generalization across diverse agricultural landscapes. The findings underscored the growing importance of deep learning in precision agriculture, enabling automated, large-scale crop monitoring with improved accuracy and efficiency.

Yao et al. [10] explored large-scale crop mapping using multi-source optical satellite imagery combined with machine learning techniques and discrete grid-based analysis. The study introduced an efficient methodology for crop classification by leveraging high-resolution satellite data and advanced feature extraction methods. By integrating multiple optical data sources, the approach improved classification accuracy and minimized issues related to missing or inconsistent data. The discrete grid system allowed for structured data representation, enhancing spatial resolution and precision in crop type differentiation. The study demonstrated that machine learning algorithms, including random forests and gradient boosting models, effectively captured complex patterns in agricultural landscapes. The results highlighted the potential of multi-source satellite imagery and AI-driven techniques in large-scale agricultural monitoring, providing valuable insights for policymakers and researchers in precision farming and land-use management.

Zhao et al. [11] investigated paddy rice area mapping in regions characterized by persistent cloud cover and heavy rainfall by employing a spatiotemporal data fusion technique combined with a phenology-based algorithm. The study addressed the major challenge of limited optical satellite visibility in cloudy environments by integrating multi-temporal datasets to reconstruct clear surface observations. The fusion method enhanced the temporal continuity of satellite imagery, allowing for more reliable extraction of rice growth signatures across different stages of cultivation. By leveraging phenological characteristics such as transplanting and heading periods, the approach effectively distinguished paddy fields from other land cover types. The algorithm demonstrated strong robustness in cloudy and rainy regions, consistently producing high-accuracy rice area maps. The findings highlight the significance of spatiotemporal fusion and phenology-based analysis in overcoming climate-related data gaps, contributing valuable advancements to agricultural monitoring and remote sensing-based crop mapping in challenging environmental conditions.

2. Proposed methodology

The methodology employed in developing a model for the paddy field detection focuses on guaranteeing robustness, accuracy, and user-friendly crop management tools in the designed system architecture. It begins with rigorous data handling, encompassing collection, cleaning, and augmentation. A hybrid CNN-EfficientNetB1 model is designed and trained, and key metrics for evaluation. Fig. 1 shows the process flow of this methodology.

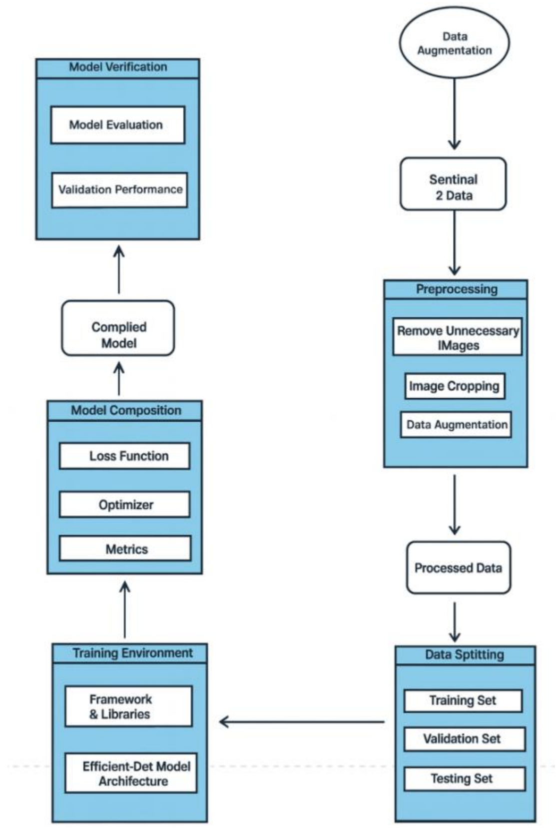

Fig. 1. Process flow model

2.1. Data collection and preprocessing

Sentinel-2 Imagery: There is no data set available for the AP region, which leads to manually collecting the images. Accessing Sentinel-2 data through Google Earth Engine (GEE) and Google Earth Pro. Focusing on the growing seasons for paddy and cotton in Andhra Pradesh. Considering historical data for previous years to capture seasonal variations. Using the AP GIS portal for boundaries and location of fields for labelling purposes and annotation. Q-Gis is useful for dividing the images into small tiles from a large image.

2.2. Data augmentation

For the data labelling, we used the Python labelling tool, which supports the Pascal-VOC format, which is an XML file. We labelled all the images. Data augmentation, including random flips and rotations, was applied to diversify the dataset, improve the model's ability to generalize, and mitigate the risk of overfitting.

2.3. Data loading and processing

Filtering: Remove unwanted data like clouds, cloud shadows, or snow cover that can interfere with classification accuracy. Utilize cloud masking tools available in GEE. Atmospheric Correction: Correct for atmospheric effects that distort the spectral characteristics of land cover features. Data Preprocessing. Filtering: Remove unwanted data like clouds, cloud shadows, or snow cover that can interfere with classification accuracy. Utilize cloud masking tools available in GEE. Due to limitations for collecting data, the small amount of collected samples can be augmented to increase the dataset size. Techniques can involve duplicating the images and (image rotation, flipping, etc). The available tool is RoboFlow.

2.4. Model creation

The creation of an effective paddy field detection model involves several stages, including data preprocessing, model selection, training, and evaluation. For this project, the EfficientDet model was chosen due to its balance between accuracy and computational efficiency. EfficientDet is a deep learning-based object detection model that utilizes a compound scaling approach, making it well-suited for satellite image analysis. The training dataset consists of Sentinel-2 satellite images, which were pre-processed to enhance feature extraction. This preprocessing included resizing and normalization to ensure uniform input size, as well as cropping and labelling, where relevant regions of the images were annotated in the Pascal VOC format and later converted into the TensorFlow Object Detection format using RoboFlow. To improve the model's generalization ability, data augmentation techniques such as flipping, rotation, and brightness adjustments were applied. EfficientDet is a powerful deep learning model designed for object detection tasks, combining efficiency with high detection accuracy. It is built upon the Efficient Net backbone, which optimizes the trade-off between accuracy and computational cost. One of its key innovations is the Bi-Directional Feature Pyramid Network (Bi-FPN), which enhances feature fusion across different scales, allowing the model to detect objects of varying sizes more effectively. Unlike traditional detection models, our proposed model uses a compound scaling approach, jointly scaling depth, width, and resolution to achieve better performance with fewer computational resources.

ALGORITHM 1 EFFICIENT- DET ALGORITHM

Input: Pre-Satellite image dataset I= [I1, I2, …, In] where each Ii is a satellite image

Output: Bounding box coordinates and class labels B= [B1, B2, …., Bn] for detected paddy cr

1: For i=1 to n do, Load the images Ii.
2: Preprocess the images (resize, normalise, and augment). Ii
3: Extract image features using Efficient-Det backbone (Bi-FPN).
4: Predict bounding boxes, confidence scores, class probabilities.
5: Use Non-Maximum Suppression (NMS) to get rid of overlapping boxes. Store final bounding boxes Bi with class labels and scores. Return bounding boxes B, class labels associated with them, and the confidence scores.

2.5. Model training

EfficientDet was chosen for this project due to its ability to handle high-resolution satellite images while efficiently detecting paddy fields across large geographic regions. Its lightweight nature enables faster inference without compromising accuracy, and the use of Bi-FPN ensures better detection even in complex agricultural landscapes where fields vary in size and shape. The model was trained on a labelled dataset of Sentinel-2 satellite images, where paddy fields were manually annotated. To enhance generalization, image augmentation techniques such as random cropping, flipping, and contrast adjustment were applied during preprocessing. The training process involved fine-tuning the model using transfer learning, starting from pre-trained model weights to accelerate convergence. Optimization was carried out using the Adam optimizer with learning rate decay to ensure stable training, while loss functions helped improve detection accuracy. enabling seamless predictions of new data with the acquired knowledge.

2.6. Model evaluation

The performance of the trained model was evaluated using standard metrics to ensure accuracy and reliability in detecting paddy fields from Sentinel-2 satellite images. Key evaluation metrics included Mean Average Precision, where mAP@50 and mAP@75 were used to assess how well the predicted bounding boxes aligned with ground truth annotations. Average accuracy was measured to quantify detection accuracy, while precision and recall were analysed to determine the model's effectiveness in correctly identifying paddy fields and minimizing missed detections. The F1-score provided a balanced evaluation of precision and recall. Quantitative results showed a high accuracy of 86 percent and mean average precision values exceeding 85%, demonstrating strong detection capabilities. A precision-recall analysis indicated that the model effectively minimized false positives while maintaining high recall. Qualitative analysis through visual inspection confirmed accurate identification of paddy fields with minimal false detections, though minor challenges were noted in areas with mixed land cover, such as paddy fields adjacent to water bodies or non-agricultural lands.

2.7. EfficientDet

EfficientDet is a state-of-the-art object detection model designed for high accuracy and computational efficiency, making it ideal for large-scale applications such as satellite image analysis. It employs a compound scaling approach that balances the depth, width, and resolution of the network, ensuring optimal performance without excessive computational demands. One of the key advantages of EfficientDet is its use of the Bi-directional Feature Pyramid Network (Bi-FPN), which enhances feature fusion across multiple scales, allowing the model to effectively detect objects of varying sizes, including small and irregularly shaped paddy fields. Additionally. These characteristics make it well-suited for processing high-resolution satellite images, where efficient computation and precise detection are crucial. The model's ability to generalize well across different landscapes and environmental conditions further supports its application in agricultural monitoring. In the context of paddy field detection, this model proves advantageous as it can accurately differentiate between cultivated lands and surrounding non-agricultural areas, even in complex and fragmented landscapes. The model's lightweight nature allows for faster inference times, enabling near-real-time monitoring of vast agricultural regions, which is essential for timely decision-making in crop management. Additionally, its adaptability through transfer learning enables it to be fine-tuned with relatively small amounts of labelled data, reducing the need for extensive manual annotation. Overall, the model's balance between computational efficiency, accuracy, and scalability makes it a powerful tool for remote sensing applications, particularly in agricultural monitoring, where precise and timely crop detection is essential for resource optimization, food security, and sustainable farming practices. We also trained some basic models like Yolov5 and CNN to compare the accuracy and we got more accuracy in this model than normal models.

3. Results

3.1. Training accuracy and loss graphs

This section demonstrates the results of the proposed system in a detailed manner. This project created a model that can detect the paddy fields, as shown in the figures below. This information can be used to improve agricultural practices by optimizing resource allocation and promoting sustainable farming methods, ultimately leading to increased productivity shown in Fig. 3.

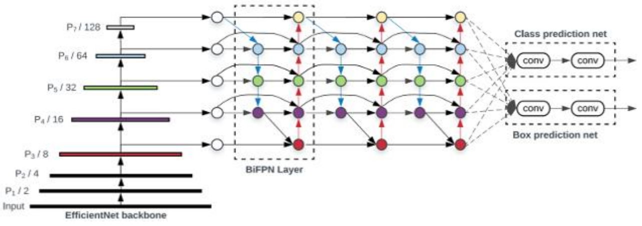

Fig. 2. EfficientDet architecture – it employs Efficient Net as the backbone network, Bi-FPN as the feature network, and a shared class/box prediction network. Both Bi-FPN layers and class/box net layers are repeated multiple times based on different resource constraints, as shown in the above figure

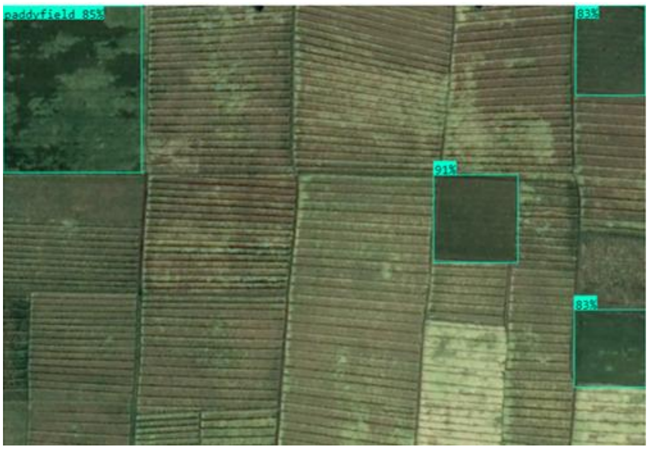

Fig. 3. Detection on the image

3.2. GUI Output

Fig. 4 and 5 show the output and training graphs showing accuracy, and we have achieved more than 85 percent accuracy. Fig. 6 shows the GUI of the model. Table 1 shows the comparison of our proposed model with other models like YOLOv5 and Faster RCNN. Hence, we achieved an overall accuracy of 86 percent.

Fig. 4. Output

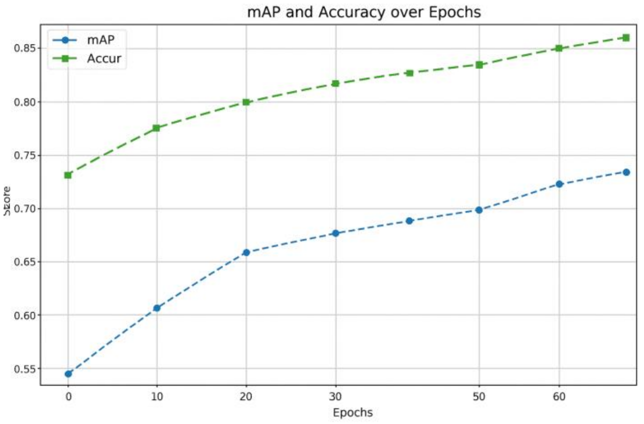

Fig. 5. Graph showing results

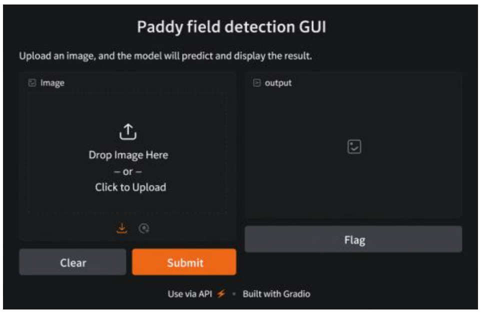

Fig. 6. Graphical user interface

Table 1. Comparison with other models

Model	Accuracy
EfficientDet-D1 (Proposed)	0.86
YOLOv5-S	0.81
Faster-RCNN (ResNet-50)	0.83

4. Conclusions

This project successfully developed a new paddy field detecting model that leverages remote sensing data and object-based classification rules. The model achieved a higher accuracy compared to traditional pixel-based methods, demonstrating its effectiveness in identifying paddy fields from satellite imagery. Additionally, rule-based classification based on rice phenology. This makes the model's decision-making process more transparent and easier to understand compared to complex machine learning models. While there might be limitations such as the reliance on training data and computational demands, this research offers a significant contribution to the field of paddy field detection. The improved accuracy and interpretability of the model show the way for its potential application in various agricultural and food security efforts. Future work could involve incorporating additional data sources and validating the model in different regions. Overall, this project has taken a promising step towards more robust and transparent methods for mapping paddy fields using remote sensing technologies. The project's success paves the way for exciting future endeavours. Researchers could explore incorporating high-resolution satellite imagery for even finer details about paddy fields or utilize radar data to identify flooded fields and monitor soil moisture. Additionally, machine learning techniques could streamline the development of the model's fuzzy rules, while expert knowledge could be incorporated into an expert system to guide and refine these rules. Furthermore, testing the model in regions with diverse rice practices and environmental conditions is crucial for wider applicability.

Finally, developing a user-friendly interface would make this tool accessible to a wider range of users, from agricultural professionals who can utilize it for crop monitoring and resource planning to policymakers who can leverage it for informed decision-making on food security and agricultural development. These future directions hold immense promise for making this paddy field detection model a powerful tool for various stakeholders.

Limitations and transferability: Although our model achieved strong performance, certain limitations must be acknowledged. The training data was derived from selected regions of Andhra Pradesh, which may restrict the model's generalization capability in areas with different climate conditions, crop varieties, and other characteristics. Another challenge is that the presence of mixed land cover may result in reduced confidence in terms of transferability. The model can be adapted to other regions by applying domain adaptation and fine-tuning using region-specific sampling. For deployment in regions with different cropping patterns, incorporating multi-temporal imagery and fine-tuning would further enhance robustness and generalization.

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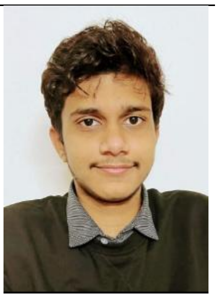

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